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Optimization of Incung Ancient Manuscript Character Recognition Using Template Matching and Image Enhancement

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Abstract: *Ancient manuscripts represent valuable cultural heritage but are highly vulnerable to physical degradation and loss of public understanding. One such heritage is the Incung script manuscripts from Kerinci Regency, Indonesia, which remain underexplored in digital recognition research. This study proposes an optimized integration of image enhancement, template matching, and Convolutional Neural Network (CNN) methods to improve the accuracy and stability of Incung character recognition. Image enhancement is applied to improve contrast and legibility, template matching is used to capture structural character patterns, and CNN is employed as a complementary classifier to validate recognition results. Experimental results on segmented character images show that the proposed approach achieves a training accuracy of 93% and a validation accuracy of up to 100% with stable loss values, indicating effective learning under controlled conditions. Although performance decreases when applied to full manuscript images due to segmentation challenges and low contrast, the proposed method demonstrates strong potential for digital preservation of Incung manuscripts. While this study does not directly implement smart city services, the resulting digital manuscript data can support local wisdom–based smart city initiatives by enabling digital cultural documentation and access.*

Keywords: *Ancient Manuscripts, Smart City, Enhancement, Template Matching,CNN, Culture*

1. Introduction

Indonesia is an archipelagic country characterized by substantial cultural diversity, in which cultural spaces and local traditions function as integral components of community identity and sustainable development discourse [1]. This diversity is manifested in regional languages, customary systems, and indigenous writing traditions transmitted intergenerationally. In recent years, traditional Nusantara scripts have attracted increasing scholarly attention, particularly through digital documentation and computational recognition initiatives aimed at cultural preservation [2]. Within the broader framework of Southeast Asian manuscript studies, community-driven preservation efforts and academic research remain central to sustaining the continuity of local written heritage [3]. One example of such local heritage is the traditional Kerinci script originating from Kerinci Regency, Jambi Province. Historically, Kerinci manuscripts were inscribed on organic materials such as tree bark, buffalo horns, palm leaves, and bamboo [4]. These manuscripts encompass literary texts, customary regulations, ritual expressions, and local knowledge systems, thereby constituting a significant component of Kerinci cultural identity. Nevertheless, ongoing transformations in literacy practices and the rapid expansion of digital technology have contributed to declining familiarity with the script, particularly among younger generations, raising concerns regarding its long-term preservation and sustainability[5].

To address this challenge, Kerinci Regency is developing a Smart City concept that integrates technology into various aspects of life, including smart governance, smart economy, smart environment, smart people, smart mobility, and smart living. Preserving local culture can be achieved through the digitization of ancient manuscripts, which is expected to broaden public knowledge, introduce the younger generation to cultural richness, and become part of sustainable development [6], [7].

In the context of digitalization, digital image processing plays a crucial role, particularly template matching and enhancement methods. Template matching functions to match image patterns with templates [8] and has been widely used in the identification of letters[9], faces [10], number [11], fingerprints [12] and other applications [13], [14], [15]. Research [14], successfully recognized characters with CNN using 1,400 images across 28 classes, achieving 99% training accuracy and 91% testing accuracy. Research[15], applied template matching with IMM hashing for fingerprints. Research [10] developed a neighborhood pool method for FPGA-based face detection with significant efficiency improvements. Research [17] identified palm lines using template matching and K-NN with an accuracy of 86.67%. Template matching was also used in vehicle license plate detection with an accuracy of 84% and a speed of 0.942 milliseconds [18].

Enhancement methods have also been shown to improve image processing results. In research [11], a combination of symmetric hashing and a dynamic threshold algorithm improved fingerprint security and accuracy. Research [19] developed a three-stage detection system for vehicle icons that achieved nearly 99% accuracy by combining template matching and local change detection.

Although template matching and CNN-based recognition methods have been widely studied, most existing works focus on modern scripts or general image recognition tasks and commonly rely on single-method or partially integrated approaches [4], [8] Research specifically addressing ancient manuscripts, particularly Incung script manuscripts from Kerinci, remains very limited due to unique character shapes, degraded media conditions, and the lack of publicly available datasets [4]. These limitations reduce the robustness of existing methods when applied to low-quality manuscript images. To address this gap, this study proposes an optimized and structured integration of image enhancement, template matching, and CNN methods specifically designed for the characteristics of Incung manuscripts. The proposed approach represents a novel contribution by combining classical pattern-based techniques and deep learning within a unified recognition framework for underrepresented ancient scripts.

Based on the identified research gap, this study aims to develop an optimized recognition framework for ancient Incung manuscripts by integrating image enhancement, template matching, and CNN methods. This framework is expected to improve recognition accuracy under degraded manuscript conditions and support the digital preservation of Kerinci cultural heritage.

2. Research Method

This study adopts a structured research framework consisting of several sequential processes, as illustrated in Figure 1.

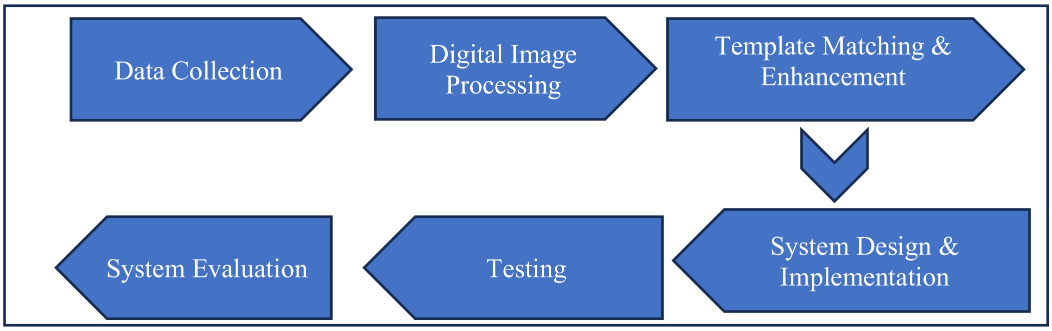

Figure 1. Research framework of the proposed Incung script recognition system

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As shown in Figure 1, the proposed framework consists of several sequential stages, including data collection, digital image processing, template matching and enhancement, system design and implementation, testing, and system evaluation. Each stage is designed to ensure accurate recognition of Incung script characters while maintaining robustness against variations in manuscript quality.

2.1 Data Collection

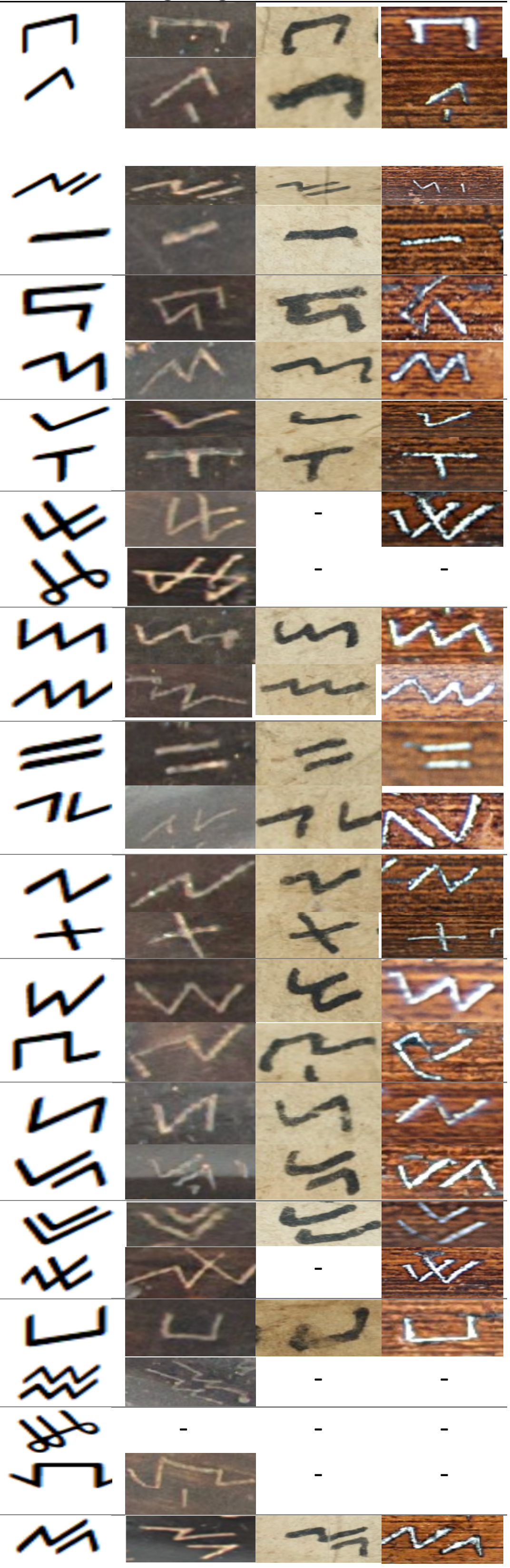
At this stage, Incung script imagery was collected from the digitization of ancient manuscripts from various sources, such as the Depati Sungai Laga Inscription, the Daluwang Manuscript, bamboo media, and references to the Westenenk Incung script. This digitization process yielded hundreds of individual letter images from manuscript cuts, which were then divided into training and test data. The goal of this data collection was to obtain a diverse dataset, encompassing differences in letter shape, ink thickness, and manuscript media condition (from clear to degraded). This ensured that the resulting dataset could represent the actual condition of the Incung script. In total, 1.240 segmented Incung character images were obtained from the digitization process and grouped into 24 character classes. Each class contains between 32 and 78 samples, reflecting natural variations and class imbalance commonly found in historical manuscripts. The manuscript images exhibit varying physical conditions, including clear, moderately faded, and degraded states due to aging and writing media characteristics. All segmented characters were manually annotated and validated based on standardized Incung script references prior to being used for training and testing.

(a) (b) (c)

Figure 2. (a)Prasasti Depati Sungai Laga & (b)Bambo (c) Daluwang
Source: (British Library, https://eap.bl.uk/archive-file/EAP117-2-1-2)

Figure 2 shows representative examples of Incung script manuscripts used in this study, illustrating variations in writing media and physical conditions. Table 1 summarizes the composition and distribution of the Incung script image dataset used for training and evaluating the proposed recognition model.

Table 1. Incung Script Image Dataset



Latin	Script Westenenk	Prasasti Depati Sungai Laga	Naskah Daluwang	Bambo
Ka				
Ga				
Nga				
Ta				
Da				
Na				
Pa				
Ba				
Ma			-	
Ca			-	-
Ja				
Nya				
Sa				
Ra				
La				
Wa				
Ya				
Ha				
A/Ha				
Mba				
Mpa				
Nda			-	
Nta				
Nja			-	-
Nca		-	-	-
Ngka			-	-
Ngga				

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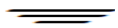
Latin	Script Westenenk	Prasasti Depati Sungai Laga	Naskah Daluwang	Bambo
Ngsa				

Table 1 presents the detailed composition of the Incung script dataset, including the number of samples per character class, which forms the foundation for model training, validation, and performance evaluation

2.2 Digital Image Processing

After the images are collected, the next stage is digital image processing. The goal is to improve the visual quality of the script so that it can be better recognized by a computer system. The image processing stages in this study include:

1. Enhancement
   The enhancement process is carried out to emphasize the contrast between the letters and the background of the manuscript. This technique helps reduce visual disturbances caused by media aging, stains, or physical damage to ancient manuscripts. By increasing the contrast, the letterforms become clearer and more consistent, making them better recognized by the system.
2. Binarization
   Colored or grayscale images are converted into black-and-white binary images. This process is performed by determining a threshold so that the letters appear black, while the background becomes white. This binarization stage is important to simplify visual information and focus detection only on letter patterns.
3. Image Morphology
   Morphological operations, such as dilation, erosion, and closing, are applied to improve the structure of the letters. These techniques serve to close small gaps in the strokes of the letters, remove noise, and emphasize the contours of the letters. This allows the initially blurred or disjointed letterforms to be reconstructed to a more complete form.

This pre-processing stage produces higher quality letter images which facilitates accurate segmentation and feature extraction in the subsequent recognition stage.

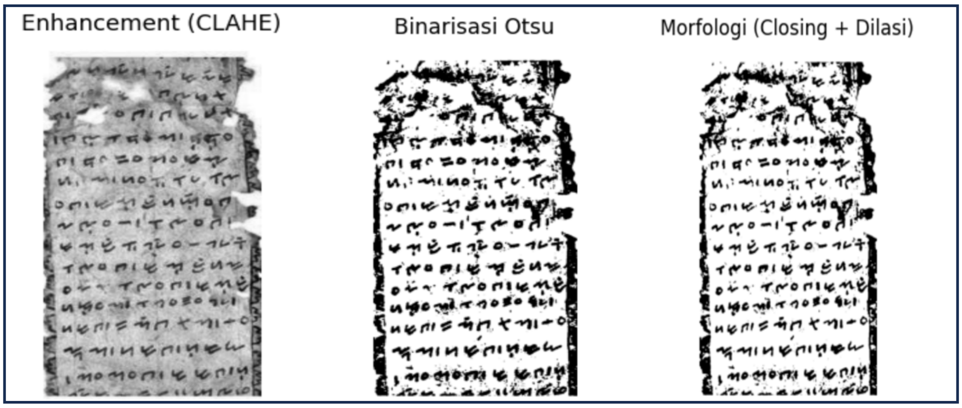


Figure 3. Enhancement Process, Binarization, Image Morphology

Figure 3 illustrates the sequential preprocessing stages applied to the Incung manuscript images, including enhancement, binarization, and morphological operations, which aim to improve character clarity prior to segmentation.

2.3 Segmentation

After going through the pre-processing stage, the Incung script images were then segmented by manually cutting each letter from the ancient manuscript. This segmentation process aims to separate each letter so that it can be used as input data in the model training process. The results of the letter cutting are then classified according to their labels based on the Latin letters they represent, as in Table 1 (the letters ka, ga, nga, and ta). This segmentation process produces a well-structured Incung script image dataset. The obtained dataset was then divided into two parts:

1. Training Data
   Used to train the letter recognition model. This training data was augmented with augmentation techniques, such as rotation, flipping, resizing, and lighting adjustments, to make the model more robust to variations in letter shape and conditions in the script.
2. Testing Data
   Used to test the model's performance after training. The test data consisted of letters not included in the training data, providing an objective picture of the system's accuracy in recognizing the Incung script.
   The training and test data were separated proportionally, with a general ratio of approximately 80% of the data used for training and 20% for testing. This stage is crucial to avoid overfitting and ensure the model can recognize new letters with a good level of accuracy. Segmentation was performed manually to ensure accurate character labeling; however, this approach limits scalability and may not directly generalize to full-manuscript recognition.

2.4 Experimental Environment

All experiments were conducted on a MacBook equipped with an Apple M1 processor running macOS version 15.6.1 and 24 GB of RAM. Image preprocessing and template matching were implemented using OpnCV, while the Convolutional Neural Network (CNN) model was developed, trained, and evaluated using TensorFlow and Keras. The experiments were executed in a Python-based environment to ensure reproducibility.

3. Results and Discussion

The training phase was conducted using a Convolutional Neural Network (CNN) designed to recognize visual patterns in Incung script images. The segmented dataset was divided into two parts, consisting of 80% training data and 20% testing data, which were fed into the CNN architecture for training and evaluation. This section presents the experimental results obtained from the proposed method, including the model training process and performance evaluation based on segmented Incung script images.

3.1 Results

This subsection presents the experimental results obtained from the proposed method, focusing on the training process and performance of the CNN-based recognition model on segmented Incung script images.

3.1.1 Model Training Process

During the training phase, the training data were processed over several epochs to optimize the network weights. To increase data diversity and reduce the risk of overfitting, data augmentation techniques were applied, including small rotations (±10–15°), horizontal and vertical translations, and variations in lighting intensity. After 10 epochs, the model achieved a training accuracy of 93% and a validation accuracy of up to 100% on the segmented character dataset.

3.1.2 Model Evaluation

Model evaluation was conducted on a dataset consisting of 24 classes of segmented single-character Incung images. The evaluation metrics used include accuracy, precision, recall, and F1-score, which were computed based on aggregated classification results across all classes. The evaluation metrics used include accuracy, precision, recall, and F1-score, which are defined as follows:

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$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}, \text{Precision} = \frac{TP}{TP+FP}, \text{Recall} = \frac{TP}{TP+FN}, \text{and F1-Score} = \frac{2PR}{P+R}. \quad \textbf{(1)}$$

With TP=24 and TN=FP=FN=0

The accuracy, precision, recall, and F1-score values all reached 1.00 (100%), indicating that the model is stable and very effective in recognizing visual patterns of letters in the enhanced images, with a minimum loss of 0.0019. These results were obtained on segmented single-character images under controlled experimental conditions.

3.1.3 Visualization of Detection Results

To analyze model performance during the training process, accuracy and loss values were monitored on the training data and validation data at each epoch. A visualization of the relationship between the number of epochs and accuracy and loss values is presented in Figure 4. This graph provides an overview of the stability and convergence of the model's learning process in recognizing Incung character patterns.

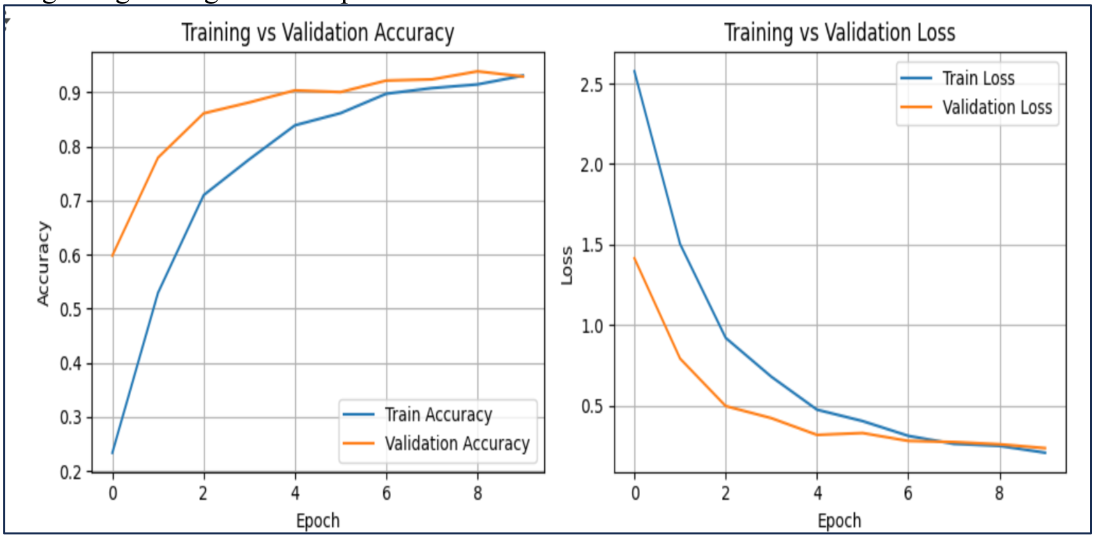

Figure 4. Training vs Validation Accuracy Graph & Training vs Validation Loss Graph.

In Figure 4, the graph on the left shows the progression of training accuracy (Train Accuracy) and validation accuracy (Validation Accuracy) versus the number of epochs. Training accuracy increased gradually until it reached approximately 93%, while validation accuracy reached 100% at the 10th epoch. The consistent increase in both curves indicates a stable and convergent learning process under the given experimental conditions. The graph on the right shows a significant decrease in both training loss (Train Loss) and validation loss (Validation Loss) with increasing epochs.

The consistent and unidirectional pattern of loss reduction between training and validation data indicates stable learning behavior under the given experimental conditions. It should be noted that these results were obtained using segmented single-character images under controlled experimental conditions.

To understand the model's ability to recognize each character in the Incung script, a confusion matrix analysis was performed. A confusion matrix was used to evaluate class-level recognition performance, as shown in Figure 5.

Based on the confusion matrix in Figure 5, it can be seen that all predicted values are on the main diagonal, indicating that each Incung script character was correctly recognized by the model. There were no classification errors observed on the validation data, resulting in up to 100% accuracy under controlled experimental conditions. These results demonstrate that the combination of the Enhancement and Template Matching methods, supported by a CNN architecture as a complementary classification tool, effectively improves the recognition performance of Incung script character images.

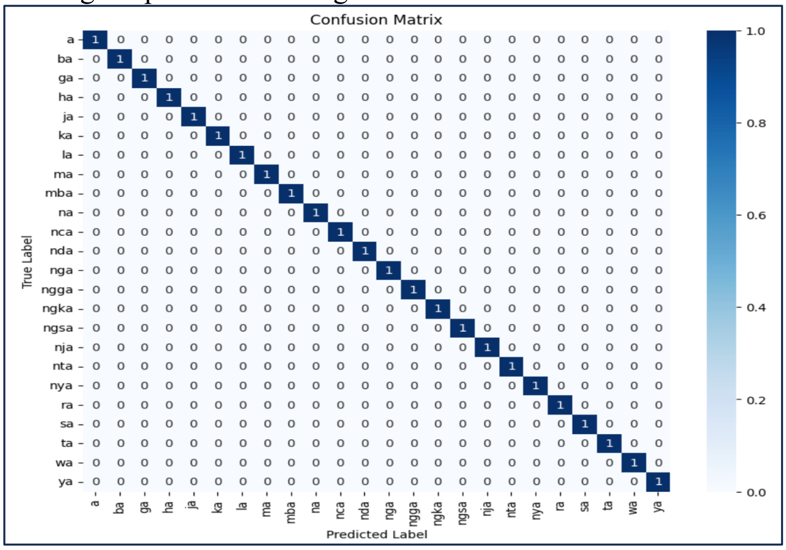

Figure 5. *Confusion Matrix*

3.1.4 Visualization of Detection Results

The CNN model was able to classify Incung script characters with a very high level of confidence in each test class. Figure 6 shows several model prediction results for the test characters, demonstrating consistent classification performance across different Incung character classes.

Each test character was successfully classified correctly according to its original label, demonstrating the model's ability to recognize visual patterns of the Incung script consistently and precisely.

3.2 Discussion

This sub-chapter discusses the interpretation of the experimental results, factors influencing model performance, comparisons with related studies, and the contribution of the proposed approach. The experimental results show that the proposed model achieved a training accuracy of 93% and a validation accuracy of up to 100% on segmented single-character Incung script images. These results indicate that the proposed approach is effective under controlled experimental conditions, with stable learning behavior as reflected by low loss values and the absence of misclassification in the confusion matrix. The obtained performance can be attributed to the integration of image enhancement and template matching prior to CNN-based classification. Image enhancement improves character–background contrast and reduces degradation effects, while template matching preserves the fundamental structural patterns of Incung characters. This preprocessing combination provides more representative inputs for the CNN, enabling more effective feature extraction. The findings of this study are consistent with previous research on traditional script recognition. Previous studies have reported accuracy above 98% for Batak Toba script recognition using CNN on segmented characters[19]. Similarly, related work has demonstrated that CNN performs well for Sasak script classification, highlighting the importance of data variation and augmentation [20]. Other studies have also reported approximately 98% accuracy in Bima script recognition using CNN [21] . These studies support the effectiveness of CNN-based approaches for traditional script recognition when combined with appropriate preprocessing. In a broader context, studies on ancient script recognition have shown that more complex architectures such as CNN–LSTM and CapsNet–LSTM are required for ancient scripts with overlapping characters and high structural variability [22]. This aligns with the findings of the present study, where optimal performance was achieved on segmented single-character images, while challenges remain for full manuscript recognition. Despite the promising

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results, the proposed approach is still limited by segmentation quality. Dense character spacing, complex backgrounds, and noise in full manuscript images remain challenging. Overall, this study contributes a hybrid framework that integrates image enhancement, template matching, and CNN for Incung script recognition. Unlike studies relying solely on CNN, this approach emphasizes pattern-based preprocessing to improve recognition stability, supporting digital preservation efforts for local cultural heritage.

4. Conclusions

The research results show that optimizing of Template Matching and image Enhancement methods in digital image processing improves the recognition performance of Incung script characters from ancient Kerinci manuscripts. The proposed model achieved a training accuracy of 93% and up to 100% validation accuracy after ten epochs under controlled experimental conditions, with stable loss values indicating consistent learning behavior. Image enhancement effectively improves manuscript contrast and visual clarity, while template matching preserves distinctive character patterns, as reflected by the confusion matrix results. A Convolutional Neural Network (CNN) was employed as a complementary component to strengthen the classification process and validate recognition results. The integration of classical pattern-based techniques and deep learning enhances the system's reliability in handling variations in Incung script characters. However, performance on full manuscript images remains limited due to close character spacing and heterogeneous contrast conditions. Future research should focus on adaptive segmentation strategies and larger, more diverse datasets to improve robustness and generalization. Overall, this work contributes to the digital preservation of Kerinci cultural heritage and provides a technological foundation for digital cultural documentation that can support local wisdom–based smart city initiatives in Kerinci Regency.

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